

Article

Smart Highway Pilots, Carbon Emissions, and Air Pollution: Evidence from China

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Abstract

The digitalization and intelligent transformation of transportation have emerged as technological solutions for enhancing traffic efficiency and reducing traffic-related pollutants. However, existing studies primarily focus on traditional traffic emission reduction measures, and there is limited empirical evidence demonstrating how the digitization and intelligence of road infrastructure can reduce carbon dioxide emissions and air pollutants. To address this research gap, this study employed a difference-in-differences methodology to investigate the causal effects of the Smart Highways Pilot (SHP) policy on carbon emission intensity (i.e., CO₂ emissions per unit of GDP) and air pollution (i.e., PM_{2.5} concentrations), using data from 272 Chinese cities spanning 2012 to 2023. Our estimation results demonstrate that the implementation of the SHP policy led to an average reduction of about 4.7% in CO₂ emissions per unit of GDP and a 5.1% decrease in PM_{2.5} concentrations, translating to an average annual abatement of approximately 707,008 tons of CO₂ and a 2.204 µg/m³ drop in PM_{2.5} concentrations among the sample pilot cities. Furthermore, the carbon reduction and pollution mitigation effects of the SHP policy were more pronounced in regions emphasizing pilot themes, such as infrastructure digitalization and vehicle–road collaboration, cities promoting new-energy vehicles, and eastern regions. This study provides robust causal evidence for policymakers to assess the synergistic carbon abatement and pollution reduction benefits of SHP policies, while contributing to the literature on smart transportation and sustainable development, and offering valuable insights for other countries and regions on building green, low-carbon transportation systems through the digitalization and intelligent upgrading of road infrastructure.

Keywords: smart highway; carbon emissions; air pollution; particulate matter; difference-in-differences



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1. Introduction

Greenhouse gas emissions and air pollution are two major hurdles impeding efforts to promote global sustainable development, posing significant threats to climate stability, the ecological environment, and public health [1,2]. According to the Emissions Gap Report 2025, released by the United Nations Environment Programme (UNEP), global greenhouse gas emissions reached a record high of 57.7 billion tons in 2024, representing a 2.3% increase compared to 2023—significantly higher than the 1.6% increase observed between 2022 and 2023 [3]. In 2023, exposure to air pollution was responsible for 7.9 million deaths worldwide, making it the second leading risk factor for mortality across the globe,

surpassed only by high blood pressure; although prevalent globally, pollution-related mortality risk is especially high in low-and middle-income countries, such as China and India [4]. Effectively reducing carbon emissions and air pollution has thus become a critical task and a significant challenge for countries and cities worldwide.

Transportation, as a major consumer of fossil fuels, significantly contributes to carbon dioxide (CO₂) emissions and particulate matter (PM) pollutants. In 2024, the transportation sector became the second-largest source of global CO₂ emissions, surpassed only by the power sector, accounting for 15% of the total emissions that year [3]. In 2024, the total emissions of carbon monoxide, hydrocarbons, nitrogen oxides, and PM from road vehicles in China reached 12.856 million tons [5]. As the world's largest carbon emitter and the country with the highest number of motor vehicles, China has long prioritized the transportation sector as a key area in which carbon emissions and air pollution should be reduced. To this end, China has implemented a series of significant measures, including vehicle restrictions [6], the promotion of new-energy vehicles [7,8], the upgrading of green and intelligent transportation infrastructure [9,10], and the implementation of a public transit priority strategy [11,12]. In particular, the Ministry of Transport (MOT) of China issued the "Notice on Accelerating the Pilot Program of the New Generation National Traffic Control Network and Smart Highways" in February 2018, which was initiated by the launch of a smart highway construction pilot projects in nine regions, including Beijing, Hebei, Jilin, Jiangsu, Zhejiang, Fujian, Jiangxi, Henan, and Guangdong [13]. Since the implementation of this program, significant progress has been made in areas including the digitalization of highway infrastructure, integrated vehicle–road collaboration, and comprehensive management of the road network based on big data. For example, the average accident rate on the Wuxi section of Jiangsu Province's Provincial Road No. 342 decreased by 28.6%, construction efficiency on the Jinhua section of Jiangsu Provincial Road No. 420 increased by more than 10%, and fuel consumption decreased by over 25% [14]. Another example is the Suzhou section of the Jiangsu Shanghai-Nanjing Expressway, where unmanned compaction intelligent maintenance construction technology and an intelligent control system were implemented, resulting in a 6% improvement in construction accuracy, a 20% reduction in cost, and a 100% construction qualification rate [15]. Although the Smart Highway Pilot (SHP) policy has been continuously implemented for many years and yielded remarkable results, there are currently very few empirical evaluations of its outcomes. To address this gap, this study aims to empirically investigate the impact of the SHP policy on carbon dioxide emissions and air pollution by employing a difference-in-differences approach.

In contrast to the existing literature, there are several particularly valuable contributions from this study. First, to the best of our knowledge, this study is the first empirical investigation into the carbon reduction and pollution mitigation effects of China's SHP policy. Given that China is the largest emitter of CO₂ and faces significant challenges in reducing its carbon emissions and pollution, this contribution is nontrivial. Second, by providing empirical evidence of the effects of SHP policies on the reduction of carbon emissions and pollution, and by revealing their potential heterogeneity, our research also informs the evaluation of policy impacts on traffic-related carbon and pollutant emission reductions in the transportation economics literature [8]. In contrast to the prior studies that have primarily focused on traditional transportation emission reduction measures—such as road tolls [16], driving restrictions [17,18], and transit-oriented development [19,20]—our research provides empirical evidence of how the digitization and intelligentization of road infrastructure could reduce CO₂ emissions and air pollutants. Third, our research contributes to the rapidly growing body of work on the environmental impacts of transportation digitization and intelligence by providing robust causal empirical evidence [21,22]. Unlike most existing studies that primarily rely on analytical models or

digital transportation indices to explore the potential environmental benefits of digital transportation facilities and intelligent transportation systems [9,10,23], our research utilizes a quasi-natural experiment involving China's SHP policy to examine its causal impact on CO₂ emission intensity and PM_{2.5} concentration. This approach enables us to reliably discern causal relationships and thus document robust empirical evidence from a large sample of 272 Chinese cities regarding the carbon reduction and pollution mitigation effects of smart highway construction.

The structure of this article is as follows. Section 2 contains the literature review, while Section 3 introduces the policy background and theoretical framework. Section 4 details the data and methodology, followed by Section 5, which reports the empirical results, including the series of robustness tests and heterogeneity analyses. Finally, Section 6 presents the conclusions and policy implications. The research framework is shown in Figure 1.

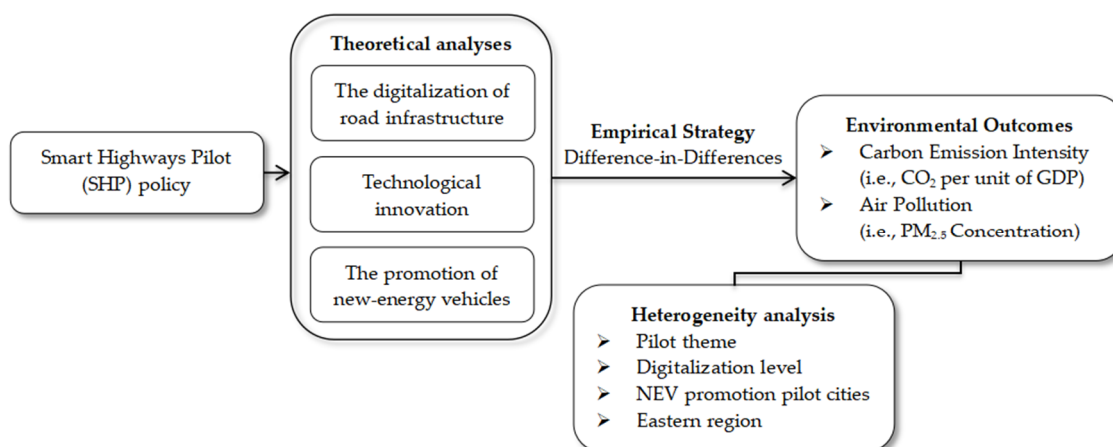


Figure 1. Research Framework.

2. Literature Review

As a major source of greenhouse gas emissions and air pollutants in urban areas, the transportation sector has long been the focal point of government reduction efforts. The significant challenges of lowering CO₂ and pollutant levels in this sector have also attracted extensive scholarly attention, leading to numerous studies that can be categorized into four groups. The first stream of literature comprises a series of studies that examine the impact of traffic-related regulatory measures on urban CO₂ emissions and air pollution, such as road pricing [16,24], driving restrictions [17,18], and low-emission zones [25,26]. For instance, using daily data from before and after the outbreak of the COVID-19 pandemic, Chen et al. (2021) found that private vehicle restriction policies substantially reduced air pollution levels, particularly those targeting local fuel vehicles or certain license plate numbers [6]. A more recent study by Basso et al. (2021) also found that a hybrid restriction format in Santiago could generate annual air quality-related benefits of approximately 500 million dollars by reducing traffic emissions [27]. In contrast to these studies, which primarily assess the environmental impacts of traditional traffic regulation measures, our research aims to evaluate the potential carbon and pollution reduction effects resulting from the digital and intelligent transformation of road infrastructure.

The second body of literature focuses on examining the environmental effects of transportation infrastructure, including inter-city railways [28,29] and intra-city public transit systems, such as bus rapid transit [30,31], light rail [30,32], and subways [33,34]. For example, based on empirical evidence from 98 medium-sized European cities, Fageda (2021) found that cities with new light rail systems experienced 3% lower air pollution and 7% less traffic congestion on average compared to cities without such systems [32]. By

analyzing data from 256 prefecture-level cities in China between 2009 and 2021, He et al. (2025) demonstrated that the high-speed rail network effectively reduced overall carbon emissions [35]. However, based on data from 315 cities in China between 2010 and 2020, Ou et al. (2024) found that increased accessibility to high-speed rail significantly raised carbon emissions in the transportation sector [36]. In contrast to the approach of these studies, our research focuses on assessing the impacts of digitally and intelligently upgrading road infrastructure on carbon emissions and air pollution.

The third stream of literature comprises an increasing number of studies that evaluate the effects of transportation electrification on emissions and pollution reduction [8,37]. For instance, by employing propensity score matching combined with a difference-in-differences model, Zhang et al. (2022) demonstrated that promoting the adoption of electric vehicles in public transit and public services can significantly reduce urban transportation carbon emissions [38]. Similarly, Ercan et al. (2022) found that the adoption of autonomous electric vehicles could reduce traffic-related greenhouse gas emissions by up to 34% by 2050, based on a hybrid simulation model applied to 929 metropolitan and micropolitan areas in the U.S. [39]. In other studies, Yang et al. (2023) and Cui et al. (2025) investigated the impacts of terminal electrification on urban CO₂ emissions and air quality in China, consistently demonstrating that terminal electrification helps reduce carbon emissions and air pollutants in the transportation sector [40,41]. However, through a simulation analysis, Lu et al. (2023) showed that the electrification of transportation fleets does not necessarily lead to decarbonization and may actually (albeit unintentionally) increase carbon emissions if implemented without a carbon price [42]. This finding is further supported by a recent study by Hao and Liu (2025), who utilized a quasi-natural experiment based on China's Ten Cities, Thousand Vehicles project to demonstrate that promoting new-energy vehicles by increasing local electricity demand actually led to an increase in urban CO₂ emissions [43]. While collectively, these studies are valuable for investigating the potential effects of vehicle electrification, our research aims to examine the carbon reduction and pollution mitigation impacts of SHP policies.

The fourth cluster of studies, which is most closely related to our study, encompasses the increasing interest in investigating the potential benefits of the digital and intelligent transformation of transportation systems [44,45]. For example, through a systematic review of the roles of blockchain and AI technologies, Singh et al. (2022) asserted that these technologies can be fully applied to address the challenges currently faced by transportation systems, such as improving energy efficiency [46]. Based on preference data from a choice experiment, Lee et al. (2023) emphasized the significant potential of vehicle-to-everything communication technologies in road transportation systems to reduce PM and greenhouse gas emissions [47]. In another study using a life cycle assessment method, Guerrieri et al. (2020) found that smart highways significantly reduce energy consumption and pollutant emissions compared to conventional highways [23]. Taking a different approach of integrating an intersection traffic simulation model with a comprehensive modal emission model, Liu et al. (2020) evaluated the environmental impact of intelligent transit priority and found that all three strategies—the active strategy, the real-time strategy, and the intelligent vehicle-infrastructure cooperation system-based strategy—significantly reduced energy consumption and carbon emissions [48]. What these studies share is the dependence of their analytical models on simulation or scenario analyses, and their results are largely contingent upon the parameter settings.

To date, only a few empirical studies have investigated the potential environmental impacts of digital transportation infrastructure and intelligent transportation systems [21,49,50]. Using panel data from 30 Chinese provinces, Zhao et al. (2022) and Ling et al. (2024) both found that intelligent transportation systems significantly reduce

carbon dioxide emissions [10,51]. Similarly, a more recent study by Liu et al. (2025) demonstrates that digital transportation facilities can reduce pollution emissions in economically developed areas [9]; however, their impact on less-developed regions is not significant. The limitation of all these studies is their measurement of the level of intelligence or digital transportation by constructing an index system, which is highly subjective and thus may not accurately reflect the real situation. For instance, the indicators used to measure the intelligent transportation index—such as the number of public transit vehicles, private vehicle ownership, road area, traffic ridership, consumer price index, and transportation expenditure—do not appear to have a direct correlation with the local level of intelligent transportation [10]. The study most closely related to our research is the recent one conducted by Lu et al. (2024), which examines the impact of China’s intelligent connected vehicle pilot policies on urban carbon emissions in a quasi-natural experimental setting [22]. While Lu et al.’s (2024) objective was to assess the environmental impact of these particular vehicle policies, our research examines the carbon and pollution reduction effects of a different intelligent transportation pilot policy in China—specifically, the SHP [22]. The intelligent transportation policy pilot we study involves not only vehicle–road collaboration, but also the digital and intelligent upgrading of transportation infrastructure, along with the application of next-generation information technologies, such as big data, 5G, and high-precision BeiDou positioning. Furthermore, our findings uncover the potential heterogeneity of this effect, providing more nuanced evidence of how intelligent transportation policies can reduce carbon emissions and pollution.

3. Policy Background and Theoretical Analyses

3.1. Policy Background

As energy consumption and greenhouse gas emissions in the transportation sector continue to increase, exploring the use of digital and intelligent technologies to achieve significant emission reductions has become a crucial strategy for promoting the green transformation of the transportation industry. In February 2018, to promote digital transformation and accelerate the development of smart highways, the Ministry of Transport of China issued the “Notice on Accelerating the Pilot Program of the New Generation National Traffic Control Network and Smart Highways,” launching SHP projects in nine provinces, including Beijing, Hebei, Jilin, Jiangsu, Zhejiang, Fujian, Jiangxi, Henan, and Guangdong [13]. This pilot policy encompasses six major themes: the digitalization of infrastructure, vehicle–road collaboration, the application of BeiDou high-precision positioning, integrated road network management based on big data, “Internet Plus” integrated road network services, and the next generation of the national traffic control network. The specific content and corresponding key implementing provinces are presented in Table 1.

Table 1. The main pilot themes of the SHP policy.

Pilot Theme	Main Content	Key Implementing Provinces
Digitalization of infrastructure	Three-dimensional measurable real-scene technology and high-precision map applications; digital collection, management, and utilization of road facilities; construction of intelligent monitoring sensor networks; and comprehensive perception, analysis, and early warning of the safety status of transportation infrastructure.	Beijing, Hebei, Henan, and Zhejiang

Table 1. *Cont.*

Pilot Theme	Main Content	Key Implementing Provinces
Vehicle–road collaboration	Intelligent upgrades to roadside systems on expressways and the integrated operation of vehicles and road infrastructure; application of 5G technology and intelligent roadside base station systems; vehicle-to-road information interaction, risk monitoring, and early warning systems; and traffic flow monitoring and analysis.	Beijing, Hebei, and Guangdong
BeiDou application	Building of BeiDou high-precision infrastructure and the implementation of long-term monitoring and early warning systems for roads susceptible to disasters; exploration of the application of highway toll collection systems based on BeiDou technology; and the development of an integrated emergency rescue management system for highways utilizing BeiDou.	Jiangxi, Hebei, and Guangdong
Road network management based on big data	Building of an intelligent management decision-making platform for highway operations and services based on big data; utilization of tools such as unmanned aircraft to enhance operational monitoring and emergency response capabilities, enabling interactive on-site information collection; conducting demonstrations of intelligent maintenance, road management, and intelligent terminals for road network incident inspection; and the development of a road network operation monitoring system.	Fujian, Henan, Zhejiang, and Jiangxi
“Internet Plus” road network services	Utilizing the “Internet Plus” technology to explore a non-stop mobile payment technology based on vehicle feature recognition; provision of value-added services like guidance and reservation for parking spaces and charging facilities in service areas using mobile internet technology; conducting a demonstration of dynamic charging for new-energy vehicles on expressways, along with precise meteorological sensing and prediction in low-temperature conditions; and the establishment of collaborative vehicle–road safety assistance services.	Jilin and Guangdong
National traffic control network	Development of a test area for safety-assisted driving and vehicle–road collaboration technologies oriented toward urban public transit and complex traffic environments; and the establishment of a physical prototype system and demonstration base for the next-generation national traffic control network.	Jiangsu and Zhejiang

3.2. Theoretical Analyses

According to the pilot themes and task contents of the SHP policy, its implementation can reduce urban carbon dioxide emissions and air pollutants through at least three theoretical mechanisms: the digitalization of road infrastructure, technological innovation, and the promotion of new-energy vehicles. First, one of the core objectives of the SHP policy is to advance the digitalization of road infrastructure. This includes the application of three-dimensional measurable real-scene technology, high-precision maps, and other information technologies to enable the digital collection, management, and application of highway facilities. Additionally, it involves constructing an intelligent monitoring sensor network to achieve comprehensive perception, analysis, and early warning of the safety status of transportation infrastructure. As such, by promoting the digitalization

of transportation infrastructure, the implementation of the SHP policy was expected to help alleviate traffic congestion and improve transport efficiency, thereby reducing urban carbon emissions and air pollution. For example, as one of the first provinces in China to implement the digital transformation and upgrading of transportation infrastructure, Jiangsu has increased highway efficiency by 10%, and through the construction of “smart stations,” the rate of special vehicle incidents has decreased to below 0.5% [52]. A recent study conducted by Liu et al. (2025) also demonstrated that digital transportation facilities can reduce pollutant emissions by enhancing traffic safety and improving traffic flow as well as socio-economic efficiency [9].

Second, technological innovation has been established as a crucial means of reducing carbon dioxide and air pollutant emissions in society [53,54]. It also serves as a fundamental mechanism that enables intelligent transportation systems to achieve carbon reduction and pollution mitigation [49–51]. An essential task in implementing the SHP policy is to promote the research, development, and application of digital intelligent technologies in the construction, operation, and maintenance of highways. For instance, the policy document clearly emphasizes the promotion of three-dimensional measurable real-scene technology, high-precision maps, and the application of 5G, as well as conducting intelligent maintenance demonstrations. Therefore, by promoting technological innovation, the implementation of the SHP policy is designed to reduce CO₂ and air pollutant emissions. For example, smart construction site applications in Jiangsu, which utilize technologies such as mobile internet, artificial intelligence, big data, and virtual reality, have enabled a reduction of approximately 500 kg of carbon emissions per kilometer of road constructed [55]. Likewise, Fuzhou, Jiangxi Province, has developed and implemented a green maintenance technology that has reduced construction costs by approximately 17.5%, decreased energy consumption by 83.7%, and lowered carbon emissions by 92.8% [56].

Third, an important task covered by the SHP policy is to provide value-added services, such as guidance and the reservation of parking spaces and charging facilities in service areas based on mobile internet. Additionally, the aim is to develop demonstration projects for dynamic charging on highways, enabling both dynamic and static charging for new-energy vehicles. Therefore, by improving the charging network infrastructure and alleviating users’ range anxiety regarding electric vehicles, the underlying idea is that the implementation of the SHP policy would promote the adoption of new-energy vehicles and thus reduce CO₂ emissions and air pollution even further [38].

4. Data and Methods

4.1. Main Variables and Data

This study employed two indicators—CO₂ emission intensity and PM concentration—to examine the effects of the SHP policy on carbon reduction and pollution mitigation. Following the approach of Ling et al. (2024), we used the natural logarithm of CO₂ emissions per unit of GDP ($\ln ECI$) to measure CO₂ emission intensity, as it eliminates the influence of economic scale and better reflects carbon emissions’ technical efficiency [51]. Consistent with the study by Wang and Fang (2025), we measured air pollution levels using the natural logarithm of the average PM_{2.5} concentration ($\ln PM_{2.5}$), as PM_{2.5} is the primary pollutant from vehicle emissions and a leading contributor to the global burden of disease [57]. For instance, a recent report indicated that 36% of the global population is exposed to environments in which PM_{2.5} levels exceed 35 µg/m³, resulting in 4.9 million deaths attributed to this exposure [4]. We collected CO₂ emission data from the Center for Global Environmental Research (CGER), which has been widely used in previous studies [58]. Our PM_{2.5} concentration data are derived from the China High Air Pollutants (CHAP) dataset (<https://chap-data.github.io/introduction.html>, accessed on 12 January 2026), which is

generated based on multi-source big data, including ground-based measurements, satellite remote sensing products, atmospheric reanalysis data, and model simulations, and employs artificial intelligence algorithms to account for the spatiotemporal heterogeneity of air pollution [59,60].

The core independent variable in our study is a binary indicator (*SHP*) that denotes whether the sample cities had implemented the *SHP* policy. In the year the sample city implemented the *SHP* policy, and in subsequent years, *SHP* takes the value of 1; otherwise, it is 0. Referring to the previous literature, we included a series of control variables that could affect urban carbon emissions and air pollutant levels to reduce the bias caused by any omitted variables [51,61–63]. The level of economic development is represented by the logarithm of the per capita regional GDP ($\ln PGDP$). Population density is defined as the natural logarithm of the total urban population divided by the area of the administrative region ($\ln POP$). The industrial structure (*IS*) is represented by the proportion of the secondary industry's output value in GDP, and governance capacity (*GOV*) is measured by the ratio of local fiscal expenditure to GDP. Technological development (*TECH*) refers to the proportion of scientific and technological expenditures relative to total local fiscal expenditure, while the consumption level (*CI*) is indicated by the percentage of total retail sales of consumer goods in the GDP. Our population density data were derived from the China Stock Market and Accounting Research (CSMAR) database, while the other control variables were sourced from the China Urban Statistical Yearbook. We excluded cities with severely missing control variable data, including Taiwan, Macao, and Hong Kong, and we used linear interpolation to fill in the few missing values in some other cities. To reduce the interference of outliers, all continuous variables were winsorized at the first and 99th percentiles. Ultimately, we obtained a balanced panel dataset covering 272 cities in China (as shown in Figure 2) from 2012 to 2023, comprising 3264 observations. The definitions and descriptive statistics of the main variables are presented in Table 2.

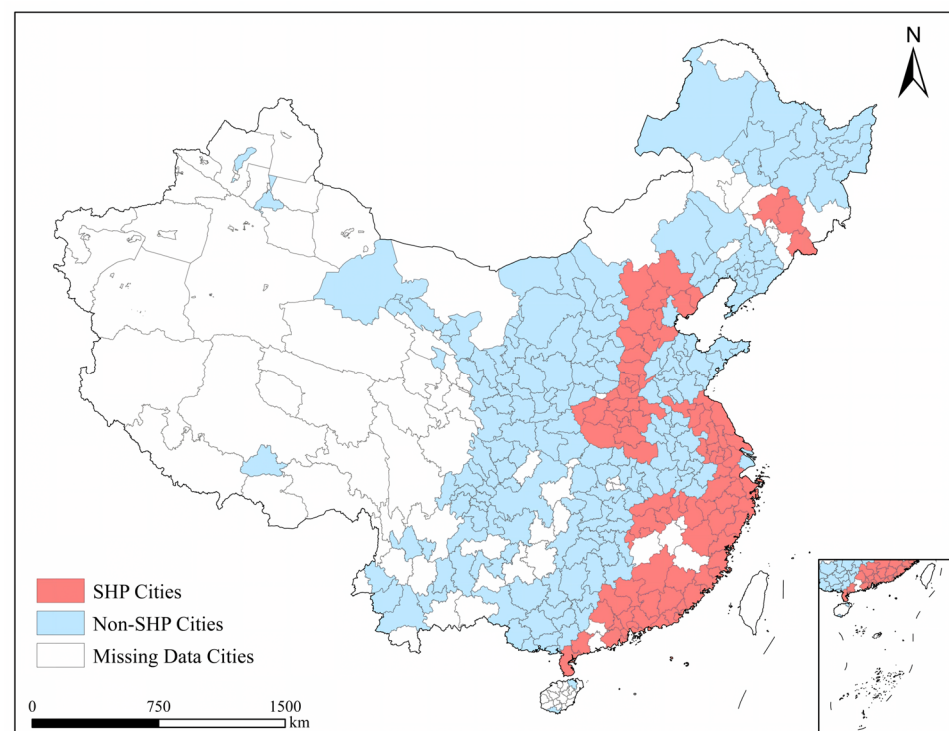


Figure 2. Geographical distribution of sample cities.

Table 2. Definitions and descriptive statistics of main variables.

Variable	Description	Mean	S.D.	Min	Max
LnECI	CO ₂ emissions per unit of GDP (tons/100 million yuan)	8.155	0.703	6.587	9.846
LnPM _{2.5}	Average PM _{2.5} concentration (µg/m ³)	3.650	0.378	2.850	4.546
SHP	Binary indicator of SHP policy implementation	0.167	0.373	0.000	1.000
LnPOP	Population density (people per square kilometer)	6.416	0.915	3.860	8.601
LnPGDP	Per capita GDP (yuan)	10.863	0.557	9.567	12.117
IS	Ratio of the secondary industry in GDP (%)	44.051	10.789	15.880	71.060
GOV	Ratio of local fiscal expenditure to GDP	0.205	0.100	0.081	0.625
TECH	Ratio of scientific and technological expenditures to total local fiscal expenditure	0.003	0.003	0.000	0.014
CI	Ratio of total retail sales of consumer goods within the GDP	0.387	0.108	0.134	0.695

Notes: N = 3264.

4.2. Methods

This study employed the difference-in-differences (DID) method to identify the causal impact of SHP policy implementation on urban carbon emissions intensity and air pollutant concentrations. By comparing pre- and post-policy changes across the treatment and control groups, the DID approach enables us to capture the net effect of the policy shock and has been widely applied in analogous policy evaluation studies [22,38]. We constructed the DID model for the baseline regression as follows:

$$Y_{it} = \alpha + \beta SHP_{it} + \delta X_{it} + \mu_i + v_t + \varepsilon_{it} \quad (1)$$

where i and t represent the city and the year, respectively, and Y_{it} is the dependent variable, representing CO₂ emissions and the average PM_{2.5} concentration in city i during year t . SHP_{it} is a binary indicator that denotes whether city i implemented the SHP policy in year t . X_{it} represents a series of control variables at the city level, such as per capita GDP, population density, and industrial structure. μ_i denotes the city fixed effect, which controls for time-invariant factors specific to each sample city, such as geographical location, and represents the time fixed effect, used here to control for common time-varying shocks that affect all sample cities, such as geopolitical conflicts. Finally, ε_{it} is the random error term, with the standard errors clustered at the city level to account for the possible serial correlation in the data [64].

One of the key hypotheses underlying the DID estimates was the parallel trend assumption, which states that the outcome variables for both the treatment and control groups would have followed the same trend over time in the absence of the SHP policy. To test this assumption, we drew on event study analysis and constructed a dynamic DID model as follows:

$$Y_{it} = \alpha + \sum \beta_k SHP_{it}^k + \delta X_{it} + \mu_i + v_t + \varepsilon_{it} \quad (2)$$

where SHP_{it}^k is a series of relative time dummy variables that take the value of 1 when the relative time distance between the SHP policy implementation date in city i and the current date t is k ; otherwise, they take the value of 0. $k < 0$ represents the period before implementation, while $k \geq 0$ represents the period afterward. The definitions of the remaining variables are consistent with those in Equation (1). Following the suggestion of Baker et al. (2022), we estimated a fully dynamic model and excluded the indicator for the most negative relative-time period (i.e., the relative time indicator from six years before the implementation of the SHP policy) to avoid perfect collinearity [65]. Obviously, β_k reflects the dynamic treatment effect of the SHP policy implementation on CO₂ emissions and the PM_{2.5} concentration (relative to the base period). If the coefficient β_k ($k < 0$) was not statistically significant, this indicated that there was no significant difference in CO₂

emissions and PM_{2.5} concentrations between the treatment and control group cities before the implementation of the SHP policy, thereby supporting the parallel trend assumption.

5. Results

5.1. Baseline Results

Table 3 presents the baseline regression results of the DID model, as specified in Equation (1). Columns (1) and (2) report the DID estimates of the impact of the SHP policy on CO₂ emission intensity and PM_{2.5} concentrations, including city and year fixed effects, but excluding the control variables. Columns (3) and (4) further account for the control variables. This stepwise specification is designed to first capture the baseline policy effect using only fixed effects, and then verify whether the estimated effects remain robust after accounting for other time-varying city-level characteristics that may confound the relationship between the SHP policy and environmental outcomes, in line with common practices in existing research [12,66,67]. It can be observed that, regardless of whether the control variables are included, the coefficient estimate of *SHP* remains negative and statistically significant at the 5% level. These results indicate that the implementation of the SHP policy significantly reduced local CO₂ emission intensity and PM_{2.5} concentrations. Since the DID estimates in columns (3) and (4) incorporated the control variables, all subsequent analyses were based on these results. Specifically, the implementation of the SHP policy resulted in an average reduction of approximately 4.7% in the city's CO₂ emissions per unit of GDP and an average decrease of about 5.1% in PM_{2.5} concentrations. Based on the average CO₂ emissions per unit of GDP (33,585 tons per billion yuan) and the average annual total GDP (447.9 billion yuan) of the sample pilot cities, we roughly estimated that the implementation of the SHP policy resulted in an average annual reduction of approximately 707,008 ($33,585 \times 447.9 \times 0.047$) tons of CO₂. Similarly, based on the average PM_{2.5} concentration data from the sample pilot cities (43.208 µg/m³), we estimated that the SHP policy resulted in an average reduction of approximately 2.204 (43.208×0.051) µg/m³ in the annual PM_{2.5} concentration.

Table 3. Baseline Regression Results.

Variables	LnECI (1)	LnPM _{2.5} (2)	LnECI (3)	LnPM _{2.5} (4)
<i>SHP</i>	−0.050 ** (0.024)	−0.052 *** (0.008)	−0.047 *** (0.011)	−0.051 *** (0.008)
LnPOP			−0.025 ** (0.010)	−0.001 (0.008)
LnPGDP			−0.488 *** (0.042)	−0.029 * (0.017)
<i>IS</i>			−0.005 *** (0.001)	0.001 ** (0.001)
<i>GOV</i>			1.508 *** (0.214)	−0.068 (0.078)
<i>TECH</i>			−12.586 *** (2.329)	−1.579 (1.817)
<i>CI</i>			0.077 (0.065)	−0.029 (0.032)
Constant	8.164 *** (0.004)	3.659 *** (0.001)	13.554 *** (0.496)	3.957 *** (0.183)
Observations	3264	3264	3264	3264
R-squared	0.965	0.974	0.988	0.974
Time FE	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Control	NO	NO	YES	YES

Notes: Robust standard errors clustered at the city level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.2. Parallel Trend Assumption

To test the parallel trend assumption, we estimated the dynamic treatment effects of the SHP policy implementation using the event study-DID model specified in Equation (2), and the estimation results are presented in Figure 3. It is evident that the coefficient estimates of β_k ($k < 0$) are not statistically significant, indicating that there was no significant pre-treatment trend in the carbon emission intensity and PM_{2.5} concentrations of the treatment and control group cities before the policy's implementation. This finding supports the parallel trend assumption. In addition, we observed that the carbon reduction and pollution mitigation effects of the SHP policy exhibited a certain lag: The CO₂ emissions and PM_{2.5} concentrations in the pilot cities only began to show significant decreases in the second year following the policy's implementation. An intuitive and reasonable explanation is that the tasks involved in implementing the SHP policy—such as digitizing transportation infrastructure and constructing new-energy vehicle charging stations—require time and are unlikely to be completed immediately after the policy is enacted.

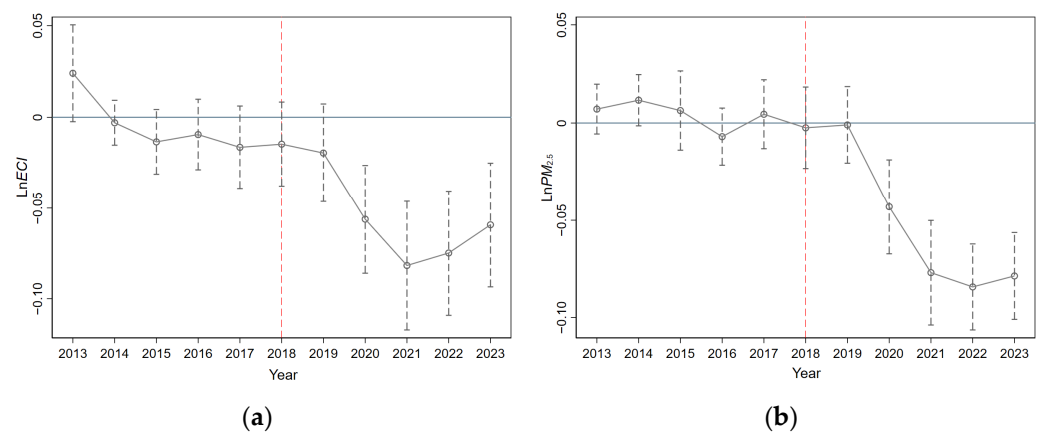


Figure 3. Results of dynamic treatment effects. Figures (a) and (b), respectively, present the dynamic treatment effect estimates using CO₂ emissions per unit of GDP and PM_{2.5} concentration as the dependent variables. The vertical red dashed lines represent the implementation date of the SHP policy, with the 95% confidence interval shown, and standard errors clustered at the city level.

5.3. Robustness Tests

5.3.1. Propensity Score Matching

One potential concern is that the selection of pilot areas for the SHP policy is not random but instead influenced by observable characteristics, such as the level of economic development and the completeness of transportation infrastructure, which could introduce selection bias. To this end, following common practice in the existing literature [66,68], we conducted a DID estimation based on propensity score matching (PSM). Specifically, using population density (LnPOP), economic development (LnPGDP), industrial structure (IS), governance capacity (GOV), technological development (TECH), and consumption levels (CI) of the sample cities in 2017 as matching variables, we employed a logit model to estimate the propensity scores and conducted one-to-one matching without replacement. Then, we re-ran our DID estimation using the matched samples, and the results are presented in columns (1) and (2) of Table 4. Consistent with our baseline results, the coefficient estimates of SHP were all significantly negative.

Table 4. Results of robustness tests.

Variables	PSM-DID		Other Related Policies		Exclude After 2019		Replace the Dependent Variable	
	LnECI (1)	LnPM _{2.5} (2)	LnECI (3)	LnPM _{2.5} (4)	LnECI (5)	LnPM _{2.5} (6)	LnPCD (7)	LnPM ₁₀ (8)
<i>SHP</i>	−0.037 * (0.019)	−0.025 ** (0.011)	−0.053 *** (0.011)	−0.053 *** (0.008)	−0.027 *** (0.008)	−0.016 ** (0.007)	−0.104 *** (0.028)	−0.017 ** (0.008)
Constant	12.795 *** (0.837)	4.019 *** (0.267)	13.727 *** (0.483)	4.009 *** (0.180)	13.377 *** (0.571)	4.487 *** (0.181)	9.099 *** (0.682)	4.727 *** (0.176)
Observations	1584	1584	3264	3264	2448	2448	3264	3264
R-squared	0.980	0.982	0.988	0.974	0.990	0.977	0.951	0.974
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES	YES	YES
Control	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Robust standard errors clustered at the city level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.3.2. Other Related Policies

Another concern was that concurrent policies enacted during the research period may have influenced local CO₂ and air pollutant emissions, potentially leading to an overestimation of the *SHP* policy's impact. To this end, we created a series of dummy variables and included them as controls in our DID model to eliminate the potential effects of the Low-Carbon City Pilot (*LCP*) policies, the Broadband China Pilot (*BCP*) projects, and the Smart City Pilot (*SCP*) initiatives. For example, if a city implemented the Low-Carbon City Pilot policy in a given year, the corresponding policy dummy variable *LCP* for that city took a value of 1 for that year and all subsequent years; otherwise, it took a value of 0. Columns (3) and (4) of Table 4 present the DID estimation results after including these policy dummy variables. All coefficient estimates of *SHP* were significantly negative at the 1% level, which was consistent with the baseline results.

5.3.3. COVID-19 Pandemic

To address the potential objection that our estimation results may have been influenced by the impact of the COVID-19 pandemic on regional energy consumption and pollution emissions, we conducted additional robustness tests. Specifically, we removed sample observations made after the outbreak of the COVID-19 pandemic—that is, those occurring after 2019. We then repeated our DID estimation, and the results are presented in columns (5) and (6) of Table 4. We also excluded all sample cities in Hubei Province, the region most severely affected by the COVID-19 pandemic, where the strictest prevention and control measures were enforced. The estimated results remained consistent, and the coefficient of *SHP* was significantly negative. All the results indicate that the implementation of the *SHP* policy significantly reduced local carbon emission intensity and PM_{2.5} concentrations, which reinforced the robustness of our baseline findings.

5.3.4. Variable Measurement

To further enhance the robustness of our findings, we conducted a sensitivity analysis on the measurement of the dependent variable. Following the approaches of Chen et al. (2020) and Zhang et al. (2022), we measured carbon emission intensity using per capita CO₂ emissions (LnPCD) and air pollution levels by PM₁₀ concentration (LnPM₁₀) [17,38]. We then re-estimated the DID model, as shown in Equation (1), and the results are presented in columns (7) and (8) of Table 4. Consistent with our baseline findings, the coefficient estimate of *SHP* remained significantly negative.

5.3.5. Clustered Standard Error

In the baseline model, we clustered the standard errors at the city level to account for within-city serial correlations over time, which is also a common practice in the existing

literature [69]. We also clustered the standard errors at the provincial level, the city-year level, and at both the city and date levels. The results remained consistent with the baseline estimates, as shown in Table 5.

Table 5. Results of adjusting the standard error clustering level.

Variables	Provincial Level		City-Year Level		Both the City and Date Levels	
	LnECI (1)	LnPM _{2.5} (2)	LnECI (3)	LnPM _{2.5} (4)	LnECI (5)	LnPM _{2.5} (6)
<i>SHP</i>	−0.047 ** (0.018)	−0.051 *** (0.018)	−0.047 *** (0.006)	−0.051 *** (0.004)	−0.047 *** (0.014)	−0.051 ** (0.017)
Constant	13.554 *** (0.776)	3.957 *** (0.293)	13.554 *** (0.286)	3.957 *** (0.115)	13.554 *** (0.839)	3.957 *** (0.316)
Observations	3264	3264	3264	3264	3264	3264
R-squared	0.988	0.974	0.988	0.974	0.988	0.974
Time FE	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES
Control	YES	YES	YES	YES	YES	YES

Notes: Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$.

5.3.6. Double Machine Learning

To further enhance the reliability of our DID estimation results, we conducted a robustness test using a novel causal inference method recently proposed by Chernozhukov et al. (2018), known as the double machine learning (DML) model [70]. Here, we constructed a partial linear regression model, which was specified as follows:

$$Y = \theta SHP + g_0(X) + U, E[U|X, SHP] = 0 \quad (3)$$

$$SHP = m_0(X) + V, E[V|X] = 0 \quad (4)$$

where g_0 and m_0 are unknown interference functions estimated using machine learning algorithms, including lasso, gradient boosting, random forests, and support vector machines. U and V are random error terms. The definitions of the other variables are the same as those in Equation (1), but θ represents the average treatment effect. Table 6 presents the results of the DML estimation, which show that the coefficient estimate of *SHP* was significantly negative, regardless of the machine learning algorithm used. This indicates that the implementation of the *SHP* policy significantly reduced local CO₂ emission intensity and PM_{2.5} concentrations. This finding aligns with our DID estimation and further supports the robustness of our baseline results.

Table 6. Results of the DML estimation.

Panel A. Dependent variable: LnECI	LASSO (1)	GB (2)	RF (3)	SVM (4)
<i>SHP</i>	−0.047 *** (0.006)	−0.168 *** (0.025)	−0.099 *** (0.024)	−0.153 *** (0.024)
Constant	−0.000 (0.001)	−0.002 (0.011)	−0.003 (0.011)	0.009 (0.012)
Observations	3264	3264	3264	3264
Time FE	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Control	YES	YES	YES	YES

Table 6. Cont.

Panel B. Dependent variable: LnPM _{2.5}	LASSO (1)	GB (2)	RF (3)	SVM (4)
<i>SHP</i>	−0.041 *** (0.005)	−0.213 *** (0.017)	−0.195 *** (0.017)	−0.182 *** (0.015)
Constant	0.000 (0.001)	0.000 (0.005)	0.001 (0.005)	0.005 (0.005)
Observations	3264	3264	3264	3264
Time FE	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Control	YES	YES	YES	YES

Notes: Robust standard errors clustered at the city level are reported in parentheses. *** $p < 0.01$.

5.3.7. Placebo Test

Another objection considered was that the observed reductions in carbon emissions and pollution may be attributable to other unobserved factors, rather than being driven by the implementation of the SHP policy. To this end, we conducted a placebo test. Specifically, we randomly selected 106 cities in which to implement the SHP policy and assigned them false implementation dates. We then conducted our DID estimation and repeated this process 1000 times. The distribution of the placebo coefficient estimates, repeated 1000 times, is shown in Figure 4, which reveals that the estimated values of the placebo coefficient clustered around zero and followed a normal distribution. Furthermore, the true value of the baseline DID estimate rests in the left tail of the pseudo-regression coefficient distribution, indicating that the likelihood of the observed carbon reduction and pollution abatement effects occurring purely by chance, and not because of the SHP policy, was very low (p -value < 0.0001).

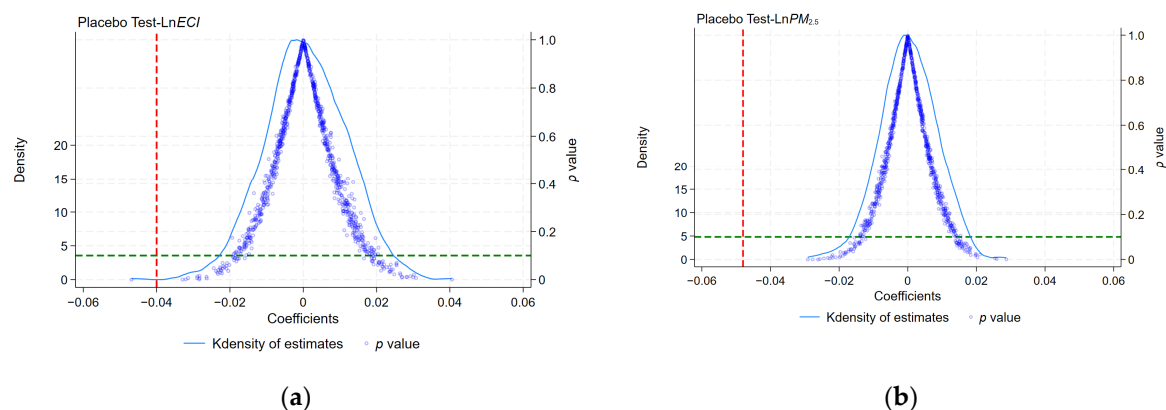


Figure 4. Results of the placebo test. Figures (a) and (b) present the placebo estimates using CO₂ emissions per unit of GDP and PM_{2.5} concentrations as the dependent variables, respectively. The vertical red dashed lines indicate the actual estimated coefficient of SHP, while the green horizontal dashed lines denote the 10% significance level.

5.4. Heterogeneity Analysis

Next, we present the results of our heterogeneity analysis to examine potential variations in the carbon reduction and pollution mitigation effects of the SHP policy across different cities. First, we investigated the potential moderating role of the pilot theme on the effects of the SHP policy. As mentioned earlier, to prevent the homogenization and fragmentation of pilot projects, the MOT of China proposed six key pilot themes for implementing the SHP policy and clearly designated those provinces in which the primary implementation would take place, as shown in Table 1. Based on the specific content of each

pilot direction, we further grouped these six themes into three categories—digitalization of infrastructure (*DI*), vehicle–road collaboration (*VRC*), and road network service management (*RNSM*)—and assigned a dummy variable to each category. For example, if the key pilot theme of the SHP policy in a sample city’s province involved the digitalization of infrastructure, the dummy variable *DI* was assigned a value of 1; otherwise, it was assigned a value of 0. Then, we multiplied these dummy variables by *SHP* and incorporated them into the model, as shown in Equation (1), and we re-estimated our DID model. As presented in Table 7, the carbon reduction and pollution mitigation effects of the SHP policy were more pronounced in areas in which the key pilot themes focused on the digitalization of infrastructure and vehicle–road collaboration. An intuitive explanation is that the *DI* theme directly targets the digital collection, management, and intelligent monitoring of road infrastructure, while the *VRC* theme focuses on facilitating real-time information exchange between vehicles and roadside infrastructure. Both contribute to optimizing traffic flow and improving transport efficiency, thereby alleviating traffic congestion and reducing traffic-related emissions. In contrast, the *RNSM* theme emphasizes administrative coordination and service optimization, which yields less direct environmental benefits. These findings also indicate that policymakers should prioritize the digital upgrading of road infrastructure and the deployment of vehicle-to-infrastructure systems to drive pollution reduction and carbon mitigation across the transportation sector.

Table 7. The potential moderating role of the pilot theme.

Variables	Digitalization of Infrastructure		Vehicle–Road Collaboration		Road Network Service Management	
	LnECI (1)	LnPM _{2.5} (2)	LnECI (3)	LnPM _{2.5} (4)	LnECI (5)	LnPM _{2.5} (6)
<i>SHP</i>	−0.046 *** (0.014)	−0.043 *** (0.008)	−0.025 (0.016)	−0.027 *** (0.008)	−0.040 *** (0.013)	−0.068 *** (0.015)
<i>SHP</i> × <i>DI</i>	−0.004 (0.016)	−0.020 * (0.011)				
<i>SHP</i> × <i>VRC</i>			−0.038 ** (0.018)	−0.040 *** (0.010)		
<i>SHP</i> × <i>RNSM</i>					−0.008 (0.014)	0.020 (0.015)
Constant	13.554 *** (0.496)	3.960 *** (0.184)	13.573 *** (0.495)	3.977 *** (0.180)	13.557 *** (0.496)	3.951 *** (0.183)
Observations	3264	3264	3264	3264	3264	3264
R-squared	0.988	0.974	0.988	0.974	0.988	0.974
Time FE	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES
Control	YES	YES	YES	YES	YES	YES

Notes: Robust standard errors clustered at the city level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Second, we investigated the potential moderating effect of the level of digital infrastructure. According to Guo et al. (2020), we measured the level of local digitalization using the Digital Financial Inclusion Index for the sampled cities [71]. Theoretically, regions with an advanced digitalization level can offer enhanced support for collecting and processing real-time traffic data, vehicle–road coordination, and big data-driven road network management services. Consequently, the carbon reduction and pollution mitigation effects of implementing the SHP policy in these areas may be more pronounced. To verify this inference, we created a dummy variable, *HighDL*, indicating whether the Digitalization Index of Inclusive Finance in the sample cities exceeded the sample median in 2017. We then multiplied this variable by *SHP*, incorporated it into the model presented in Equation (1), and repeated our DID estimation. As shown in columns (1) to (2) of Table 8, the reduction effect of the SHP policy on carbon dioxide emission intensity and PM_{2.5} concentration was more pronounced in cities with higher levels of digitalization. This finding also implies that the carbon reduction and pollution mitigation effects of the SHP policy are conditional on

the maturity of a city's underlying digital ecosystem. Cities with robust digital foundations can accelerate the deployment and integration of intelligent transportation technologies, which in turn magnifies the associated environmental co-benefits. Accordingly, policymakers should treat digital infrastructure upgrading as a core prerequisite for less-digitized regions to fully unlock the environmental gains of smart highway initiatives.

Table 8. Results of heterogeneity analysis across various cities.

Variables	Digitalization Level		New-Energy Vehicle Promotion Pilot Cities		Eastern Region	
	LnECI (1)	LnPM _{2.5} (2)	LnECI (3)	LnPM _{2.5} (4)	LnECI (5)	LnPM _{2.5} (6)
<i>SHP</i>	0.002 (0.016)	−0.034 *** (0.012)	−0.014 (0.013)	−0.040 *** (0.009)	−0.001 (0.017)	−0.033 *** (0.009)
<i>SHP × HighDL</i>	−0.070 *** (0.017)	−0.025 ** (0.012)				
<i>SHP × NEVP</i>			−0.067 *** (0.014)	−0.022 ** (0.011)		
<i>SHP × Easterncity</i>					−0.066 *** (0.018)	−0.026 ** (0.010)
Constant	13.578 *** (0.492)	3.966 *** (0.182)	13.600 *** (0.491)	3.972 *** (0.182)	13.545 *** (0.490)	3.954 *** (0.181)
Observations	3264	3264	3264	3264	3264	3264
R-squared	0.988	0.974	0.988	0.974	0.988	0.974
Time FE	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES
Control	YES	YES	YES	YES	YES	YES

Notes: Robust standard errors clustered at the city level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$.

Next, we examined the potential moderating role of policies promoting new-energy vehicles (NEV). To promote the development of the new-energy vehicle industry and facilitate energy conservation and emission reductions in transportation, the Ministry of Finance, along with four other ministries, jointly announced two batches of pilot cities—totaling 88—in 2013 and 2014, respectively, for the promotion and application of new-energy vehicles [72]. This pilot project aimed to promote the adoption of new-energy vehicles by implementing measures such as providing purchase subsidies and offering financial support for charging infrastructure, resulting in significant reductions in carbon emissions [8]. It is important to note that our theoretical analysis indicates that implementing the SHP policy could reduce carbon emissions and air pollutants by promoting the adoption of new-energy vehicles. As such, in cities that have implemented promotion policies for new-energy vehicles, we should have observed a more significant reduction in carbon emissions and pollution resulting from the SHP policy. To this end, we used a binary indicator, *NEVP*, to represent whether a sample city was a pilot city for the promotion and application of new-energy vehicles. We then multiplied this indicator by *SHP* and included the interaction term in the DID model shown in Equation (1). As shown in columns (3) to (4) of Table 8, the SHP policy's reduction effects on CO₂ emissions and PM_{2.5} concentrations were more pronounced in cities that implemented the promotion policy for new-energy vehicles, indicating a significant synergistic effect between these two policies in achieving target reductions. An intuitive explanation is that the NEV promotion pilot program addresses the demand side by providing purchase subsidies, while the SHP policy targets the supply side by improving charging infrastructure and alleviating range anxiety through dynamic charging demonstrations and reservation services at highway service areas. The combination of demand-side incentives and supply-side infrastructure support forms a virtuous reinforcing cycle that accelerates NEV adoption and amplifies environmental benefits. Accordingly, policymakers can integrate smart highway construction with NEV promotion strategies to achieve stronger synergistic benefits in carbon reduction and pollution mitigation.

Finally, we investigated potential variations in the carbon and pollution reduction effects of the SHP policy across different regions. Specifically, based on official data from China, we divided the sample cities into two groups—the eastern region and the central-western region—and represented this division using the dummy variable *Easterncity* [73]. We then multiplied this variable by *SHP* and added the interaction term to the model, as shown in Equation (1), before repeating our DID estimation. The results, presented in columns (5) and (6) of Table 8, indicate that the carbon reduction and pollution mitigation effects of the SHP policy were more pronounced in eastern cities. A plausible explanation is that eastern cities typically have well-developed digital infrastructure and stronger financial resources to support the deployment and maintenance of smart road technologies, thereby generating more pronounced environmental benefits.

6. Conclusions and Policy Implications

Using panel data from 272 cities spanning 2012–2023, this study employed a DID model to examine the causal impact of China's SHP policy on urban CO₂ and air pollutant emissions. Our DID estimation results indicate that the implementation of the SHP policy led to an average reduction of approximately 4.7% in CO₂ emissions per unit of GDP and a 5.1% decrease in PM_{2.5} concentrations in pilot cities. These figures reveal that the implementation of this policy has contributed to an average annual reduction of approximately 707,008 tons of CO₂ emissions and a 2.204 µg/m³ decline in PM_{2.5} concentrations across the sample pilot cities. These conclusions remained valid after a series of robustness tests, including PSM, other related policies, the COVID-19 pandemic, variable measurement, and DML estimation. Compared with the findings of prior studies, the SHP policy examined in this paper exhibits significant carbon emission reduction and air pollution abatement effects. For example, existing research shows that low-carbon transport policies reduce carbon emission intensity by 1.9% [67], NEV promotion policies achieve a 4.5% reduction in demonstration cities [74], and high-speed rail generates an average 1.7% CO₂ reduction in local regions and 2.3% in surrounding areas [75]. In terms of pollution reduction, existing studies have shown that high-speed rail reduces urban PM_{2.5} concentrations by 2.8% [76], while shared e-bike platforms deliver a 4.5% reduction in PM_{2.5} levels [77]. Our heterogeneity analysis further revealed that the carbon reduction and pollution mitigation effects of the SHP policy were more significant in regions in which the pilot themes focused on the digitalization of infrastructure and vehicle–road collaboration. Moreover, these effects were more pronounced in cities with an advanced digitalization level, those that had piloted the promotion of new-energy vehicles, and in eastern regions.

Our study has important policy implications. First, the findings demonstrate that the implementation of the SHP policy has significantly reduced CO₂ emission intensity and PM_{2.5} concentrations, yielding substantial environmental benefits. Therefore, policymakers should recognize the critical role that digital and intelligent transformations in transportation play in reducing carbon emissions and pollution. They should also broaden the scope of the SHP policy and increase financial support for digital transportation infrastructure and intelligent transportation systems [10]. Second, the carbon reduction and pollution mitigation effects of the SHP policy are significantly influenced by the policy's pilot themes and the characteristics of the cities. Specifically, our study indicates that policymakers should prioritize pilot projects in areas such as the digitalization of road infrastructure and vehicle–road collaboration, particularly in eastern cities with advanced digital infrastructure. Third, our study demonstrates that the carbon reduction and pollution mitigation effects of the SHP policy are more pronounced in pilot cities that actively promote and apply new-energy vehicles. Therefore, for pilot cities with existing NEV promotion initiatives, it is particularly advisable to roll out digital and intelligent transport policies such as the SHP policy. This

approach not only boosts NEV adoption but also delivers substantial synergistic effects in reducing CO₂ emissions and traffic-related air pollutants [8]. Nevertheless, it should be noted that the construction of smart highways faces several challenges, including high investment costs, uncertain economic returns, and cybersecurity concerns [78]. For instance, China's Hangzhou–Shaoxing–Ningbo smart expressway costs approximately CNY 406 million per kilometer, nearly four times the average cost of conventional expressways [79]. Accordingly, other countries and regions—especially low-income economies with under-developed digital infrastructure and low internet penetration—should carefully evaluate potential costs and economic benefits (e.g., via cost–benefit analyses) and take full account of their own fiscal capacity before launching smart highway projects.

Our study has several limitations that should be addressed in future research. First, although our sample includes observations spanning five years following the implementation of the SHP policy, we are essentially investigating the short-term impact of this policy on urban CO₂ emission intensity and PM_{2.5} concentrations. Given the potential for demand-induced effects similar to those observed with road expansion [31,80], it would be valuable for future research to further examine the long-term environmental impacts of such policies. Second, although we have identified the carbon and pollution reduction effects of the SHP policy and explored its potential heterogeneity, we are unable to fully elucidate its mechanisms of action due to limitations in data availability. For instance, by facilitating the exchange of vehicle–road information and enabling traffic flow monitoring, analysis, and warnings, we argue that implementing the SHP policy could also help alleviate traffic congestion, decrease energy consumption, and consequently reduce carbon emissions and traffic-related air pollutants [10,50]. Therefore, we call for future research to investigate these potential mechanisms further and provide a more nuanced understanding of their dynamics. Third, due to the lack of data on financial investments into implementing the SHP policy in the sample cities, we were unable to conduct a cost–benefit analysis or cost-effectiveness ratio. With the availability of relevant data, future research in this area would be valuable, as it could offer a more objective and comprehensive understanding of the potential benefits as well as the costs of such policies. Fourth, due to the lack of SHP policy implementation intensity data—including the share of smart highway mileage and total fiscal investment—this study also cannot conduct intensity-based DID estimation, nor can it examine the potential moderating effect of implementation intensity on the policy's carbon reduction and pollution abatement effects. We therefore encourage future research to conduct such analyses of treatment effect heterogeneity when data become available, to provide a more nuanced understanding of the policy's impacts.

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Abbreviations

The following abbreviations are used in this manuscript:

SHP	Smart highways pilot
CO ₂	Carbon dioxide
PM	Particulate matter
DID	Difference-in-differences
PSM	Propensity score matching
GDP	Gross domestic product

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